Predicting Flight Delays Using Weather

December 12, 2024
Team Data Hawks

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Research Question:

Are weather conditions an effective predictor in classifying flight delays?

Data Analysis Timeline

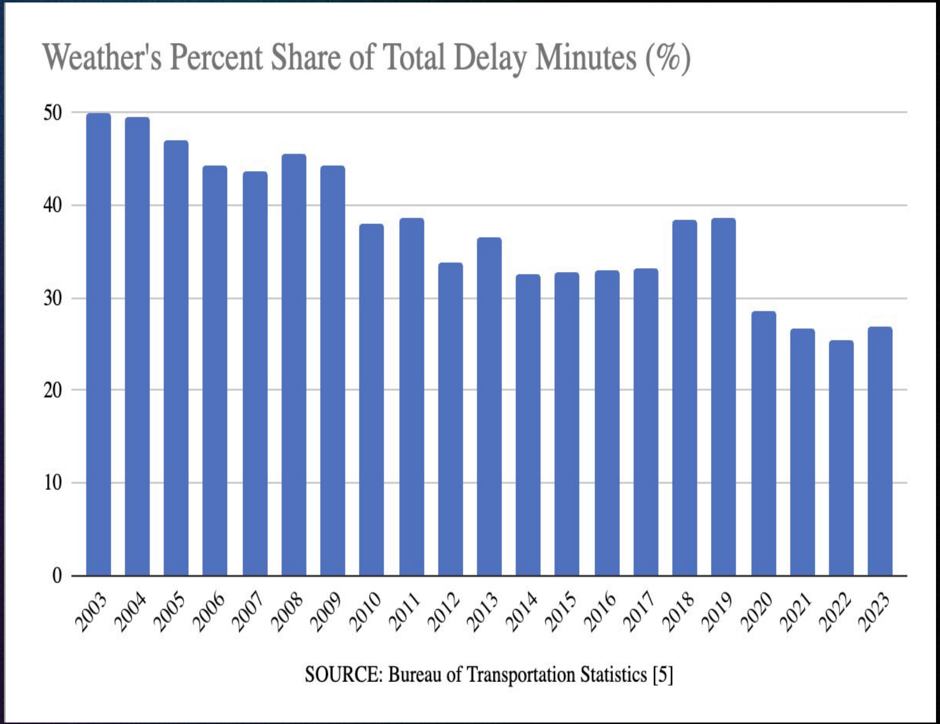
- Research and Lit Review
- Data Collection and Cleaning
- Modeling
- Results and Discussion

Impact of Weather-Related Flight Delays

1. **Delays:** Extreme weather caused 32.6% of delay minutes (2003-2015), with up to 82% in severe cases. [2]

2. **Economic Costs:** Delays cost up to $40.2B annually, including $31.2B in 2010. [3]

3. **Environmental Impact:** Idling/rerouting increase emissions and air pollution. [4]



Data Collection

Source:

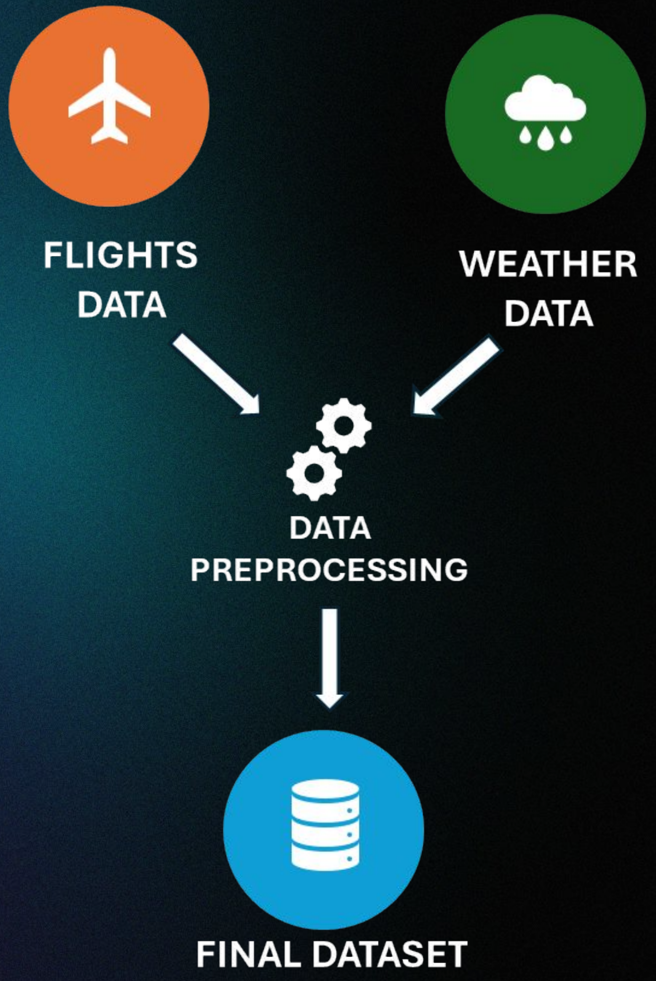
- Flight Data : Bureau of Transportation Statistics
- Weather Data : Iowa Environmental Mesonet

Merging Conditions:

- Columns: DateTime & Location

DataSet information:

- Flight Features: 18
- Weather Features: 12
- States: Illinois & Georgia (10 years)
- Size: 1 GB



Data Cleaning & Preprocessing

Flights Data:

- Dropped rows with missing data for a cleaner dataset.
- Created a datetime feature for easier condition merging.
- Converted string columns to categorical data and classified delayed flights.

Weather Data:

- Handled missing data by replacing 'M' with NaN and applying forward fill.
- Generated 15-minute intervals and filled missing data using interpolation.
- Standardized precipitation values by replacing 'T' with a small value (0.005).

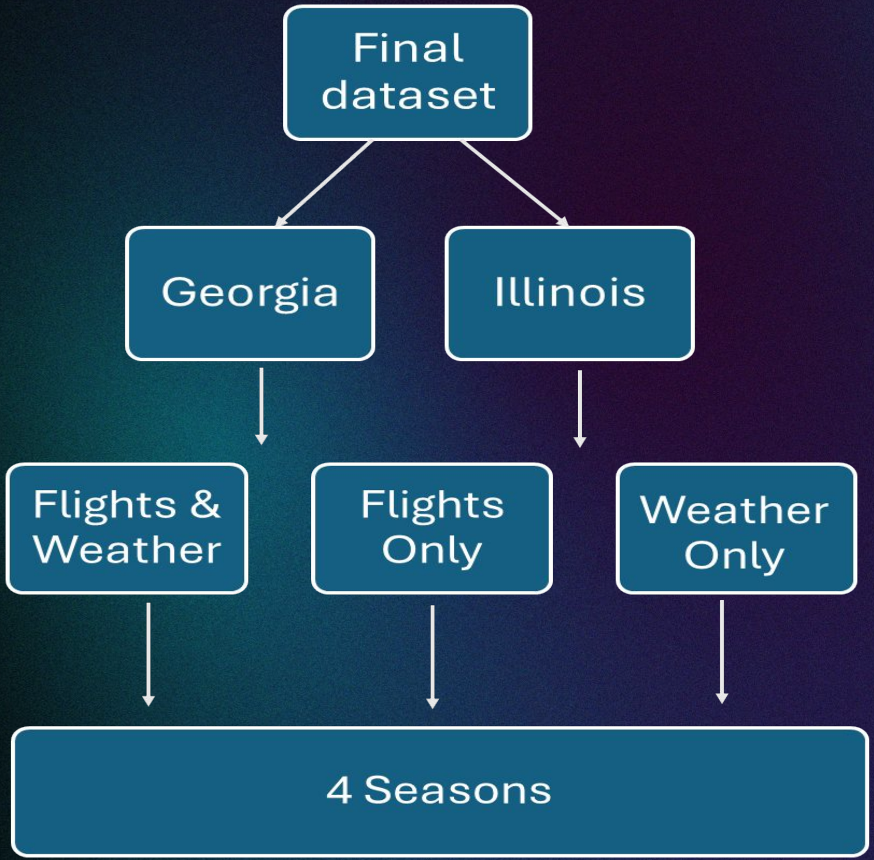
Methodology and Modeling

- Data Split (70-20-10): 10-year data split: 7 years for training, 2 for validation, 1 for testing.

- SMOTE for Balancing: Applied SMOTE to address class imbalance in the dataset.
  - Training set only

- Model Exploration: Evaluated 5 models: Logistic Regression, Linear SVC, Random Forest, Decision Tree, CatBoost.

Three Fold Method



Results

- Recall is highest using **only weather predictors**
- F-1 score is highest using **all predictors**
- <u>Highest Recall</u>: Spring in Illinois with CatBoost 0.99 & Decision Tree 0.99
- <u>Highest F1-Score</u>: Summer in Illinois with Catboost 0.56 & Full LR 0.56
- **Wind speed** and **precipitation** emerge as critical features influencing flight delays, especially during rainy months like April.

Conclusion

Weather data outperforms flight data alone in predicting delays, but combining both provides the most reliable overall predictions.

Thank you!

Dr. Edward Ochoa, Leon Shen,
Logan Gage, Jacob Crampton

References

[1] Kim, S., Park, E. Prediction of flight departure delays caused by weather conditions adopting data-driven approaches. J Big Data 11, 11 (2024).

[2] Goodman, C. J., and J. D. Small Griswold, 2019: Meteorological Impacts on Commercial Aviation Delays and Cancellations in the Continental United States. J. Appl. Meteor. Climatol., 58, 479–494

[3] Yhdego et al. "Analyzing the Impacts of Inbound Flight Delay Trends on Departure Delays Due to Connection Passengers Using a Hybrid RNN Model." Mathematics 2023, 11, 2427.

[4] Gratton, G. B. et al. "Reviewing the Impacts of Climate Change on Air Transport Operations." The Aeronautical Journal 126.1295 (2022): 209–221. Web.

[5] https://www.bts.gov/content/weathers-share-delay-percent-total-delay-minutes-year

Appendix

Feature	Data Type	Description
Year	int64	Year of the flight
Quarter	int64	Quarter of the year
Month	int64	Month of the flight
Day_of_Month	float64	Day of the month
Day_of_Week	float64	Day of the week
Operating_Carrier_Code	object	Code of the operating airline
Tail_Number	object	Aircraft tail number
Origin_Airport_ID	float64	ID of the origin airport
Origin_Airport_Code	object	IATA code of the origin airport
Origin_State_Name	object	State name of the origin airport
Destination_Airport_Code	object	IATA code of the destination airport
Destination_State_Name	object	State name of the destination airport
Scheduled_Departure_Time	float64	Scheduled departure time in minutes
Departure_Delay_Minutes	float64	Departure delay in minutes
Taxi_Out_Time_Minutes	float64	Taxi-out time in minutes
Flight_Distance_Miles	float64	Distance of the flight in miles
Departure_Datetime	object	Exact departure datetime
Scheduled_Departure_Time_Minutes	float64	Scheduled departure time in minutes
Air_Temperature_Fahrenheit	float64	Air temperature at the origin airport
Dew_Point_Temperature_Fahrenheit	float64	Dew point temperature at the origin airport
Relative_Humidity_Percent	float64	Relative humidity at the origin airport
Wind_Direction_Degrees	float64	Wind direction in degrees at the origin airport
Wind_Speed_Knots	float64	Wind speed in knots at the origin airport
Hourly_Precipitation_Inches	float64	Hourly precipitation in inches
Pressure_Altimeter_Inches	float64	Altimeter pressure in inches
Sea_Level_Pressure_Millibar	float64	Sea level pressure in millibars
Visibility_Miles	float64	Visibility in miles
Sky_Cover_Level_1	object	Sky cover description
Sky_Level_1_Altitude_Feet	float64	Sky cover altitude in feet
Apparent_Temperature_Fahrenheit	float64	Apparent temperature at the origin airport
Target	float64	Target variable for prediction

Feature Importance (Jan Illinois)

Model Used	**Highest Feature Importance**
Decision Tree	Hourly Precipitation Inches
CatBoost	Wind Speed
LinearSVC	Dew Point Temperature Fahrenheit
Logistic Regression	Day of Month
Random Forest	Tail Number

Feature Importance (Illinois April)

Model Used	**Highest Feature Importance**
Decision Tree	Hourly Precipitation Inches
CatBoost	Wind Speed
LinearSVC	Scheduled Departure Time
Logistic Regression	Day of Week
Random Forest	Scheduled Departure Time

Feature Importance (Illinois July)

Model Used	**Highest Feature Importance**
Decision Tree	Scheduled Departure Time
CatBoost	Wind Speed Knots
LinearSVC	Apparent Temperature Fahrenheit
Logistic Regression	Day of Week
Random Forest	Scheduled Departure Time

Feature Importance (Illinois October)

Model Used	**Highest Feature Importance**
Decision Tree	Hourly Precipitation Inches
CatBoost	Operating Code
LinearSVC	Scheduled Departure Time
Logistic Regression	Sky Cover Level
Random Forest	Scheduled Departure Time

Feature Importance (Georgia January)

Model Used	**Highest Feature Importance**
Decision Tree	Day of Month
CatBoost	Wind Speed Knots
LinearSVC	Dew Point Temperature (Fahrenheit)
Logistic Regression	Day of Month
Random Forest	Day of Month

Feature Importance (Georgia April)

Model Used	**Highest Feature Importance**
Decision Tree	Hourly Precipitation (Inches)
CatBoost	Wind Speed Knots
LinearSVC	Apparent Temperature (Fahrenheit)
Logistic Regression	Sea Level Pressure Millibar
Random Forest	Wind Speed Knots

Feature Importance (Georgia July)

Model Used	Highest Feature Importance
Decision Tree	Scheduled Departure Time
CatBoost	Sky Cover Level
LinearSVC	Scheduled Departure Time
Logistic Regression	Operating Carrier Code
Random Forest	Scheduled Departure Time

Feature Importance (Georgia October)

Model Used	**Highest Feature Importance**
Decision Tree	Hourly Precipitation Inches
CatBoost	Wind Speed Knots
LinearSVC	Temperature Fahrenheit
Logistic Regression	Day of week
Random Forest	Wind Speed Knots

Illinois, January:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.64	0.41	0.65	$\boxed{0.51}$
Linear SVC	$\boxed{0.65}$	$\boxed{0.42}$	0.64	$\boxed{0.51}$
DT	0.49	0.30	0.74	0.43
RF	0.57	0.34	0.60	0.44
CatBoost	0.41	0.30	$\boxed{0.87}$	0.45

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.56	0.31	0.46	0.37
Linear SVC	0.71	0.15	0.00	0.01
DT	$\boxed{0.74}$	0.0	0.0	0.0
RF	0.64	$\boxed{0.34}$	0.30	0.32
CatBoost	0.46	0.32	$\boxed{0.81}$	$\boxed{0.46}$

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.64	0.41	0.65	$\boxed{0.50}$
Linear SVC	0.75	$\boxed{0.71}$	0.16	0.26
DT	$\boxed{0.77}$	0.70	0.31	0.43
RF	0.56	0.36	$\boxed{0.73}$	0.48
CatBoost	0.66	0.42	0.53	0.47

Illinois, April:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	$\boxed{0.35}$	$\boxed{0.25}$	0.85	$\boxed{0.38}$
Linear SVC	0.28	0.23	0.90	0.37
DT	0.25	0.24	$\boxed{0.99}$	$\boxed{0.38}$
RF	0.33	0.24	0.86	$\boxed{0.38}$
CatBoost	0.23	0.23	$\boxed{0.99}$	$\boxed{0.38}$

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.62	0.32	0.56	0.41
Linear SVC	$\boxed{0.76}$	$\boxed{0.43}$	0.05	0.08
DT	0.50	0.29	$\boxed{0.78}$	$\boxed{0.42}$
RF	0.69	0.31	0.26	0.28
CatBoost	0.57	0.29	0.55	0.38

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.43	0.27	0.87	$\boxed{0.41}$
Linear SVC	$\boxed{0.73}$	$\boxed{0.37}$	0.20	0.26
DT	0.25	0.24	$\boxed{0.99}$	0.38
RF	0.36	0.25	0.88	0.39
CatBoost	0.36	0.25	0.90	0.40

Illinois, July:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.64	0.47	0.55	0.51
Linear SVC	0.62	0.46	0.65	0.54
DT	0.66	1.0	0	0
RF	0.59	0.43	0.62	0.51
CatBoost	0.49	0.39	0.88	0.54

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.63	0.46	0.60	0.52
Linear SVC	0.66	0.51	0.31	0.39
DT	0.60	0.44	0.59	0.50
RF	0.63	0.46	0.41	0.44
CatBoost	0.51	0.39	0.79	0.53

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.61	0.46	0.72	0.56
Linear SVC	0.68	0.55	0.39	0.45
DT	0.58	0.43	0.71	0.54
RF	0.61	0.45	0.62	0.52
CatBoost	0.59	0.44	0.75	0.56

Illinois, October:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.71	0.18	0.24	0.21
Linear SVC	0.72	$\boxed{0.20}$	0.29	0.24
DT	$\boxed{0.77}$	0.17	0.11	0.14
RF	0.70	0.17	0.23	0.19
CatBoost	0.16	0.15	$\boxed{0.98}$	$\boxed{0.27}$

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.48	0.19	$\boxed{0.71}$	$\boxed{0.30}$
Linear SVC	$\boxed{0.84}$	0.00	0.00	0.00
DT	$\boxed{0.84}$	$\boxed{1.0}$	0	0
RF	0.74	0.19	0.20	0.19
CatBoost	0.66	0.19	0.37	0.26

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.61	0.20	$\boxed{0.51}$	$\boxed{0.29}$
Linear SVC	$\boxed{0.85}$	$\boxed{0.46}$	0.03	0.06
DT	0.79	0.18	0.10	0.13
RF	0.78	0.19	0.14	0.16
CatBoost	0.66	0.19	0.36	0.25

Georgia, January:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.58	0.25	0.50	0.33
Linear SVC	0.59	0.25	0.51	0.33
DT	0.69	0.25	0.35	0.29
RF	0.47	0.23	0.64	0.33
CatBoost	0.31	0.22	0.91	0.36

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.58	0.24	0.49	0.32
Linear SVC	0.79	0.00	0.00	0.00
DT	0.82	1.0	0	0
RF	0.71	0.27	0.23	0.25
CatBoost	0.50	0.25	0.70	0.37

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.54	0.24	0.59	0.34
Linear SVC	0.80	0.65	0.06	0.11
DT	0.69	0.25	0.35	0.29
RF	0.73	0.33	0.33	0.33
CatBoost	0.78	0.43	0.16	0.24

Georgia, April:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.57	0.29	0.54	0.38
Linear SVC	0.60	0.29	0.47	0.36
DT	0.69	0.28	0.19	0.23
RF	0.49	0.26	0.61	0.37
CatBoost	0.31	0.24	0.92	0.39

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.59	0.31	0.57	0.40
Linear SVC	0.73	0.35	0.12	0.18
DT	0.54	0.28	0.58	0.38
RF	0.66	0.31	0.31	0.31
CatBoost	0.52	0.28	0.63	0.39

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.56	0.31	0.67	0.42
Linear SVC	0.73	0.39	0.20	0.27
DT	0.68	0.27	0.21	0.24
RF	0.65	0.32	0.41	0.36
CatBoost	0.71	0.36	0.26	0.31

Georgia, July:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.58	0.39	0.68	0.50
Linear SVC	0.61	0.41	0.63	0.50
DT	0.53	0.36	0.72	0.48
RF	0.51	0.35	0.71	0.47
CatBoost	0.49	0.36	0.83	0.50

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.62	0.41	0.61	0.49
Linear SVC	0.66	0.44	0.43	0.44
DT	0.62	0.40	0.47	0.43
RF	0.65	0.43	0.47	0.45
CatBoost	0.52	0.36	0.76	0.5

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.63	0.42	0.60	0.50
Linear SVC	0.66	0.44	0.46	0.45
DT	0.59	0.40	0.72	0.52
RF	0.62	0.41	0.55	0.47
CatBoost	0.52	0.36	0.76	0.49

Georgia, October:

Weather Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.55	0.16	0.52	0.25
Linear SVC	0.55	0.17	0.55	0.26
DT	0.63	0.17	0.39	0.23
RF	0.44	0.15	0.61	0.24
CatBoost	0.20	0.14	0.93	0.25

Flight Predictors Only:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.48	0.16	0.63	0.26
Linear SVC	0.79	0.15	0.10	0.12
DT	0.49	0.14	0.51	0.22
RF	0.79	0.22	0.20	0.21
CatBoost	0.71	0.21	0.37	0,27

Flight + Weather Predictors:

Model	Accuracy	Precision	Recall	F1-Score
Full LR	0.48	0.17	0.67	0.27
Linear SVC	0.84	0.22	0.05	0.08
DT	0.82	0.21	0.08	0.12
RF	0.79	0.21	0.17	0.19
CatBoost	0.83	0.29	0.10	0.15

Paper Formatting and Influence

Research done by Kim & Park heavily influenced the format of our paper [1]

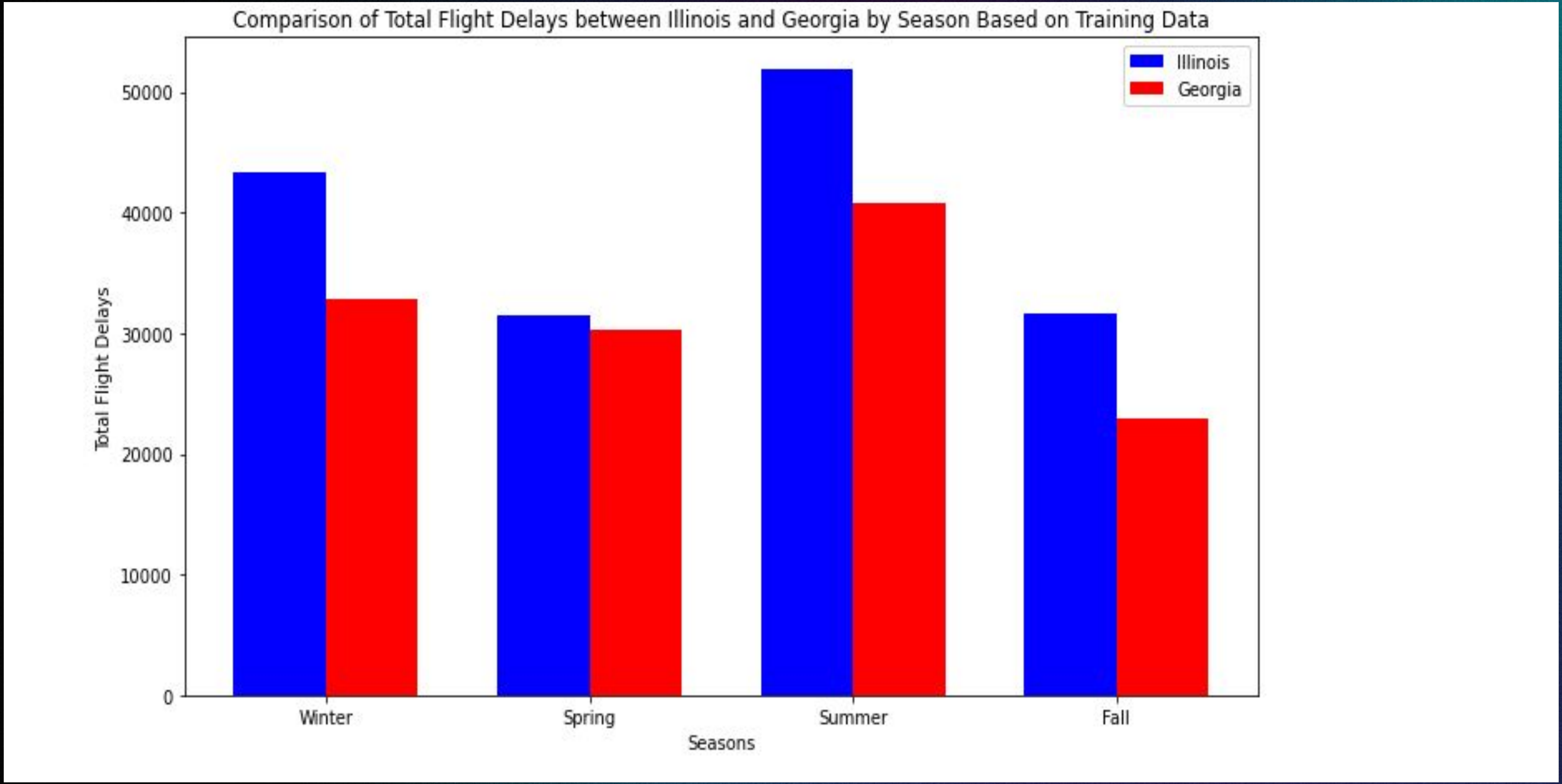
Layout and Description of Features:

Attribute mame	Description	Mean (Std)	Min	Max
Time (year)	2010–2021 (e.g. 2020)	–	–	–
Airline	Unique carrier [e.g. AA (American Airlines)]	–	–	–
Flight number	Flight number (e.g. AA2000)	–	–	–
Destination	Destination (e.g. JFK)	–	–	–
Planned departure time	Planned departure time (e.g. 1622)	–	–	–
Actual departure time	Actual departure time (e.g. 1634)	–	–	–
Result status	Takeoff intime or delay status (e.g. 1)	–	–	–
Delay type	Delay type (e.g. WeatherDelay)	–	–	–
Wind direction	Wind direction (e.g. NW, WNW)	–	–	–
Wind speed	Wind speed (e.g. 3)	10.5 (5.3)	0	51
Wind gust	Wind gust (e.g. 24)	5.3 (10.9)	0	75
Temperature (celcius)	Temperature (celcius) (e.g. 34)	51.5 (20.5)	−21	103
Dew point temperature (celcius)	Dew point temperature (celcius) (e.g. 31)	39.9 (19.5)	−32	79
Humidity	Humidity (e.g. 92)	67.7 (17.2)	0	100
Pressure (hPa)	Pressure (hPa) (e.g. 29.96)	29.3 (0.3)	0	30.2
Precipitation (mm)	Precipitation (mm) (e.g. 0.1)	0.006 (0.046)	0	2
Condition	Condition (e.g. Cloudy, Windy)	–	–	–

Layout of Important Metrics:

Algorithm		Time difference: 2 h					
		Accuracy	Precision	Recall	F1-score	Train (s)	Test (us)
DT	Normal	0.688	0.704	0.676	0.690	0.112	0.318
	Delayed		0.671	**0.700**	0.685		
RF	Normal	**0.749**	**0.729**	**0.814**	**0.769**	2.254	16.242
	Delayed		**0.776**	0.680	**0.725**		
SVM	Normal	0.651	0.631	0.774	0.695	3.625	458.280
	Delayed		0.686	0.522	0.593		
KNN	Normal	0.641	0.655	0.637	0.646	0.003	60.510
	Delayed		0.628	0.646	0.637		
LR	Normal	0.595	0.600	0.635	0.617	0.085	0.318
	Delayed		0.589	0.552	0.570		
XGB	Normal	0.721	0.715	0.759	0.736	0.150	1.274
	Delayed		0.728	0.680	0.703		
LSTM	Normal	0.644	0.620	0.776	0.689	490.4	3.503
	Delayed		0.687	0.509	0.584		

Precision	Recall
If you predict 10 flights are delayed and only 7 are actually delayed, your precision is 70%	If there are 10 delayed flights in reality and you correctly predict 8 of them, your recall is 80%


Comparison of Total Flight Delays between Illinois and Georgia by Season Based on Training Data
Illinois
Georgia
Total Flight Delays
0
10000
20000
30000
40000
50000
Winter
Spring
Summer
Fall
Seasons

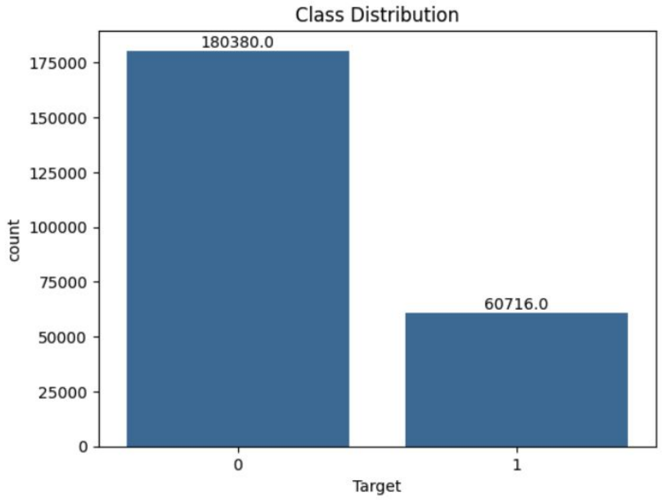


Figure 1: Class Distribution of the Dataset before SMOTE

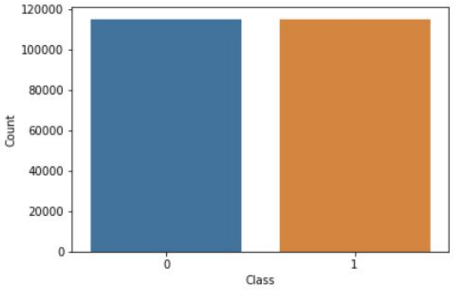


Figure 2: Class Distribution of the Dataset after SMOTE